An Examination of the Informational Value of Self-Reported Innovation Questions

by

Zheng Tian
Pennsylvania State University

Timothy R. Wojan
National Center for Science and Engineering Statistics

Stephan J. Goetz
Pennsylvania State University

CES 22-46 **October 2022**

Abstract

Self-reported innovation measures provide an alternative means for examining the economic performance of firms or regions. While European researchers have been exploiting the data from the Community Innovation Survey for over two decades, uptake of US innovation data has been much slower. This paper uses a restricted innovation survey designed to differentiate incremental innovators from more far-ranging innovators and compares it to responses in the Annual Survey of Entrepreneurs (ASE) and the Business R&D and Innovation Survey (BRDIS) to examine the informational value of these positive innovation measures. The analysis begins by examining the association between the incremental innovation measure in the Rural Establishment Innovation Survey (REIS) and a measure of the inter-industry buying and selling complexity. A parallel analysis using BRDIS and ASE reveals such an association may vary among surveys, providing additional insight on the informational value of various innovation profiles available in self-reported innovation surveys.

Keyword*:* Self-reported innovation, substantive and incremental innovation, latent innovation measure, logistic regression

JEL Classification: O00, O30

---

[*] **Disclaimer:**
Any views expressed are those of the authors and not those of the U.S. Census Bureau, the National Center for Science and Engineering Statistics, or the National Science Foundation. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2083. (CBDRB-FY22-P2083-R9621) The authors have no competing interests to declare that are relevant to the content of this article.

Acknowledgement:
This work was supported by the United States Department of Agriculture, National Institute of Food and Agriculture (USDA NIFA) under project # 2018-67023-27638. This work also supported in part by the USDA NIFA under project #2020-51150-31870 and by the Pennsylvania State University and NIFA Multistate/Regional Research Appropriations under project #NE1749.

Corresponding author:
Zheng Tian
Northeast Regional Center for Rural Development
Department of Agricultural Economics, Sociology and Education
The Pennsylvania State University
University Park, PA, 16802-5602
Email: zzt36@psu.edu

Introduction

The need for self-reported innovation data arose from the fact that patents and R&D expenditures fail to fully capture innovation processes in the modern economy. European Union countries have collected these data since 1992, with the U.S. joining in 2008, guided by the OECD's Oslo Manual which instructs national statistical agencies on how to collect this information (OECD, Eurostat, and European Union 1997; OECD and Eurostat 2005; 2018). The longer history of self-reported innovation data in Europe helps explain much greater use of these data by academics relative to the yet rare usage by U.S. academics. Another possible explanation for the reluctance to analyse self-reported innovation data in the U.S. is greater skepticism that self-reports measure innovation as commonly understood. This alternative explanation was reinforced by cognitive testing findings of European and U.S. innovation survey respondents: While European respondents generally perceived innovation as pertaining to both 'new' and 'significantly improved' products and processes, U.S. respondents were more likely to regard innovation in terms of a new product or process as different than significant improvement in an existing product or process (Peric and Galindo-Rueda 2014; Tuttle, Alvarado, and Beck 2019). If this perception extends to U.S. innovation researchers, then the self-reported innovation data may be discounted as overinclusive of the innovation phenomena of interest.

Concern that self-reported innovation measures might be overinclusive motivated the protocols used to collect and compile innovation measures in the 2014 Rural Establishment Innovation Survey (REIS). Previous research had already shown that rural and urban manufacturing firms were equally likely to implement continuous improvement and quality assurance programs (Gale et al. 1999; Wojan 1998). The research question of interest in REIS was whether rural firms were falling behind their urban peers with respect to more far-ranging innovation. To answer this question the survey included both the Oslo Manual self-reported innovation questions along with questions related to behaviour thought to be consistent with continuous improvement and more far-ranging innovation. Latent class analysis was used to statistically sort respondents into three groups: non-innovators, incremental innovators, and substantive innovators (Wojan 2016). These data provide an estimate of the potential overreporting of 'innovation' if users expect the construct to measure more than improvement.

The question examined in this paper is whether the incremental innovation measure in REIS is associated with industry characteristics that have been shown to be associated with continuous improvement; namely, the complexity of the buying and selling relationships of a given industry. The conceptual explanation for this association is that the coordination problems of firms that interact with many kinds of businesses benefit more from the systematic processes in continuous improvement programs than businesses with few different interactions. As setting up continuous improvement programs is costly, they are less likely to be present where benefits are few. A recent paper examines how this buying and selling complexity might also be associated with opportunities for innovation (Goetz and Han 2020). Their measure of 'latent innovation' also incorporates the complexity of buying and selling relationships assuming that the greater variety of interactions increases the probability of novel combinations that suggest new and better ways to do things. In these ways, buying and selling complexity may increase the opportunity, capability and need for incremental innovation.

The associations between buying and selling complexity and the various types of innovation in REIS are then compared to responses from the 2014 Annual Survey of Entrepreneurs (ASE) and the 2014

Business R&D and Innovation Survey (BRDIS) using different innovation profiles. These profiles range from new-to-market innovation suggesting a higher level of novelty that may resemble substantive innovation, to new-to-firm and process innovation that may resemble incremental innovation. Comparing responses between BRDIS and ASE also informs the question of whether joint innovation-R&D surveys tend to underreport innovation relative to innovation-only surveys (Wilhelmsen 2012). How the findings inform analysis of the current Annual Business Survey (ABS) is discussed in the conclusion of this paper.

Conceptualisation

Cognitive Testing of 'Innovation' versus 'Improvement'

In 2011 the National Center for Science and Engineering Statistics within the National Science Foundation funded an extensive cognitive testing project under the auspices of OECD's Working Party of National Experts on Science and Technology Indicators (Peric and Galindo-Rueda 2014). The objectives of the project—entitled Improving the Measurement of Innovation: Supporting International Comparisons—were to apply advances in cognitive testing and survey methodology to assess the quality and comparability of innovation data collected in national surveys complying with the Oslo Manual. The project conducted cognitive interviews with 28 European firms and 23 US firms, typically with senior managers knowledgeable of the span and depth of their firm's activities. More than two-thirds (36) of the full sample were services-providing firms with the remainder (15) in manufacturing.

Considerable attention was devoted to how respondents processed the standard innovation question: 'In the past 3 years did this firm introduce a new or significantly improved product [or process, marketing methods, etc.]?' Although both European and US respondents expressed dissatisfaction with the vagueness of 'significantly improved,' Europeans were much more likely to regard improvements as innovations.[1] American respondents were more likely to define 'innovation'—the creation of something unique—as fundamentally different than 'improvement'—the enhancement of an extant object.

While generalizing from 51 observations is problematic, information from other sources may reinforce a more confident conclusion. The numerous comments and questions pertaining to the REIS incremental innovation classification received in conference presentations and manuscript submissions

[1] The vagueness associated with "significant improvement" was corrected in the latest version of the Oslo Manual (OECD and Eurostat 2018), which now suggest the following wording for self-reported innovation questions: "a new or improved product or process (or combination thereof) that differs significantly from […] previous products or processes […]." The "significantly improved" terminology is retained in this analysis as the 2018 Annual Business Survey (developed in 2017) complied with the earlier version of the Oslo Manual (OECD and Eurostat 2005).

provide such reinforcement. With its basis in continuous improvement, many commentators suggested it was more a measure of good business practice than one of innovation. These academic comments echoed some of the quotes provided in the OECD report (Peric and Galindo-Rueda 2014 p.60):

> Our company's business model is primarily focused on continuous improvement and much less on innovation. Numerous continuing improvements can amount to large gains over time… Innovation is a different way to do things… Improvement is making the same process better.

Finally, the bibliometric evidence also suggests that the Oslo Manual definition of innovation as implemented in the EU Community Innovation Survey (CIS) has generated much more research interest than its American parallel in the Business R&D and Innovation Survey (BRDIS). *Research Policy,* the leading journal on innovation, mentions only 5 articles referencing BRDIS since its first occurrence in 2016 up through April 2022, compared to 111 articles referencing CIS over the same period. The much longer history of CIS might explain this. However, during its first 14 years of existence (1992-2006 equivalent to 2008-2022 for BRDIS), CIS was mentioned in 50 articles. There may be several explanations for the slower uptake of BRDIS relative to CIS, but a difference of an order of magnitude suggests that the positive measure of innovation prescribed by the Oslo Manual has either failed to capture the imagination of—or failed to satisfy peer review by—U.S. researchers.

Continuous Improvement as the Minimal Requirement for Incremental Innovation

The use of ‘significant improvement’ in self-reported innovation questions was criticised by respondents as being vague (Peric and Galindo-Rueda 2014; Tuttle, Alvarado, and Beck 2019). However, Deming (1982) demonstrated that the ability to assess improvement objectively depended on collection of baseline and post modification data. Lacking these data, an objectively detrimental change may be perceived as an improvement merely because it took place during a period of improving business conditions. An alternative way to assess the verisimilitude of an affirmative response to a self-reported innovation question is to also collect information on the existence of business protocols required to deem a change an improvement. This approach was used in the 2014 Rural Establishment Innovation Survey developed by USDA's Economic Research Service, and it allows two critical distinctions that are not available in the Oslo compliant surveys: 1) differentiating incremental innovators from more far-ranging innovators, and 2) differentiating self-reported innovators with the capability to objectively assess improvement from self-reported innovators with no such capability.

The incremental innovation rate reported from the 2014 REIS data is a hybrid of responses to the Oslo self-reported innovation questions and a set of questions intended to elicit the rudiments of a continuous improvement system. These data are then used as inputs for a latent class analysis that assigns membership to non-innovator, incremental innovator, and substantive innovator classes probabilistically. Thus, the ‘incremental innovation rate’ in REIS is simply the percentage of establishments in the survey most likely to be classified as incremental innovators. The method is documented and validated in Wojan (2016) and has passed numerous peer reviews (Wojan and Parker 2017; Wojan and Nichols 2018; Wojan, Crown, and Rupasingha 2018; Wojan and Slaper 2020).

Incremental innovators were likely to implement corrective actions for customer complaints regularly, assess customer satisfaction regularly, and track whether training requirements for employees were completed. Substantive innovators had similar responses to the continuous improvement questions but also were more likely to report failed or incomplete innovation projects, produce intellectual property worth protecting, and indicate capital constraints in funding innovation projects. Non-innovators were unlikely to respond affirmatively to any of these questions though many (42%) responded affirmatively to one or more of the self-reported innovation questions.

The population weighted rates across the innovation classes in 2014 were 36.8% for non-innovators, 30.1% for substantive innovators, and 33.1% for incremental innovators. The ability of REIS to break out incremental innovators from substantive innovators supports interpretation of the majority of firms in most Oslo compliant surveys that self-report as innovators (Bloch and López-Bassols 2009). More than half of these ‘innovators’ may simply be firms pursuing good business practice understood as continuous improvement. The new angle on this interpretation is that both the likelihood of implementing continuous improvement processes as well as the likelihood of discovering novel combinations of ideas underlying incremental innovation may be associated with the purchasing and selling complexity of industries.

Input-Output Complexity and Continuous Improvement

Information that contributes to innovation by combining new ideas can come from either internal sources in the form of R&D investment or external sources in the form of interaction with customers, suppliers, or competitors. Endogenous growth theory and data collection efforts have emphasised the importance of the former to understand differences in innovation rates. However, the new emphasis on open innovation suggests that external sources may be increasingly important to understand these differences.

Gómez, Salazar, and Vargas (2016) demonstrated that firms rating customers as important sources of information were more likely to generate product innovations while firms rating suppliers as important sources of information were more likely to generate process innovations using survey data from Spanish firms. The magnitude of these effects was roughly equivalent to firms rating internal sources of information as important. Goetz and Han (2020) investigated whether these findings also applied to secondary data by substituting the self-report of the importance of information with a measure of the complexity of customer and supplier relationships. Lacking microdata on the innovation orientation of firms, their ‘latent innovation’ measure is validated by constructing a geographic measure of latent innovation determined by the local industrial structure and finding an association with local per capita income and employment growth. The current analysis tests a more direct validation by incorporating the industry level latent innovation measure into the REIS microdata, allowing an examination of its association with incremental and substantive innovation.

The logic of equating an assessment of importance (Gómez, Salazar, and Vargas 2016) with that of complexity (Goetz and Han 2020) warrants an explanation given the potential to exploit secondary data to replace survey responses. If the stock of knowledge available to an individual defines some limit of its innovative capacity, then that capacity should be extended by opportunities to exchange knowledge with other individuals. In this view, innovation ‘depends…on the diversity of knowledge across individuals and on their ability to combine this knowledge, and make use of it, through complex webs of interaction' (Hausmann et al. 2013, p. 15). The greater opportunity to combine previously unrelated ideas increases this potential. An input-output table provides a useful proxy for this web of interaction as it describes the simplicity or complexity of the recipe of inputs required for a simple or complex delivery of outputs. A similar idea applies to the output (sales) side, where individual industries interact to vastly different degrees with purchasing industries.

Shannon's entropy measure is used to summarise the simplicity or complexity of these interactions in a single number (Shannon 1948; Eagle, Macy, and Claxton 2010). The measure combines the total number of other industries the target industry interacts with as well as how evenly those transactions are distributed. Entropy equals 0 when the target industry interacts with only one other industry that claims all transactions. The highest possible value would occur if a hypothetical industry divided its transactions equally among all other industries. The potential knowledge or information content of these transactions represented by the entropy value is clear. Opportunities for learning and feedback that might support innovation are greater if the target industry sells (buys) a significant share of output (input) to (from) a larger set of industries, and the more *even* the distribution of sales or purchases across industries. This mirrors the common belief that solving similar problems in slightly different contexts results in better solutions than concentrating on a single domain (Hong and Page 2004; Jeppesen and Lakhani 2010).

The latent innovation measure uses the spatial colocation of industries to capture differences in spillovers that may be facilitated by physical proximity (Delgado 2020; Kekezi and Klaesson 2020). This is done by calculating a simple correlation coefficient based on the co-location in counties of every pairwise combination of industries, which is used to discount the latent innovation measure whereby industries located at greater spatial distance have fewer opportunities for spillovers and vice versa. Finally, the industry-level latent innovation measure is adjusted by a ubiquity score reflecting how evenly the industry is distributed across the nation (Goetz and Han 2020: p. 2-3).

An industry found in every county would have a ubiquity score of 1 and an industry found in a single county would have a ubiquity score of 0. There are several alternative ways ubiquity may affect innovativeness. First, competitive pressures within an industry inducing innovation may be a function of tradability proxied by ubiquity. Competitive pressures in nontradables such as personal services can be low as importing from another region or country is not feasible. Beyond local competition there are few incentives to innovate as the market is limited. For a highly tradable industry the ability to capture a national or world market produces much greater incentives to innovate. Second, the ability of tradable industries to concentrate spatially provides advantages of scale and the localisation of highly specialised workers (Moretti 2013). Finally, the complexity of products that emerge in rare industries located in few places provide ample opportunities for the exploration of new uses and applications relative to the simpler, commonplace products produced nearly everywhere (Hidalgo and Hausmann 2009). To express the negative assumed association between ubiquity and innovation, the ubiquity score is placed in the denominator of the industry-level latent innovation measure.

The addition of the co-location correlation and ubiquity score to the core measure of input-output complexity in the latent innovation measure contributes to the spatial application of the construct. Because microlevel data on the innovation orientation of firms were not available in the first analysis of the construct, validation was tested by examining the association between a county-level aggregate of the latent innovation measure and growth in personal income and employment. The logic being that a positive association with outcome measures would support the conjecture that a higher level of regional innovation was in fact being captured by the measure. Regression analysis confirmed a precisely estimated impact of the county-level latent innovation measure on both income growth and employment growth between 2005 and 2015 (Goetz and Han 2020). Using standardised beta coefficients, the magnitude of the latent innovation coefficient estimate was only slightly less than that for the percentage of the population with a college degree; the only other variable to have a large impact in both the income and employment regressions. Patents were also included in both sets of regressions but had a much smaller impact in the income regressions and was negatively associated with employment growth. Based on these findings, Goetz and Han conclude that 'the innovation measure is picking up economic factors that are above and beyond the college achievement rate…[and] beyond creativity measures based on conventional patents.' (Goetz and Han 2020, p. 4). An examination of the latent innovation measure using microdata with information on firm innovation orientation thus appears warranted.

It is important to note that the latent innovation measure was not constructed with the intent of only characterizing innovation described as continuous improvement. While it is reasonable to assume that the learning and innovation opportunities emerging from interactions with different types of input suppliers and customers would tend toward incremental improvements, it is the potential for serendipitous discovery that the measure captures. These discoveries may spur incremental or more far-ranging innovations. However, in addition to serving as a proxy for latent innovation, input-output complexity has also been used to predict those firms most likely to seek international quality control certification known as ISO 9000 (Wojan and Bailey 1999). The standard in its most basic terms guarantees that an organisation 'says what it does and does what it says' in all aspects of its operations. Many of the objectives of ISO 9000 parallel those of continuous improvement, particularly with respect to the documentation of procedures establishing a baseline. The explicit objectives of ISO 9000 are not to spur innovation—in fact there is some evidence to suggest its emphasis on bureaucracy may thwart innovation (Gotzamani and Tsiotras 2002)–but it is reasonable to assume that certified firms will be more proficient in the discipline of continuous improvement than noncertified firms. More recent research rejects the assumption that ISO 9000 undermines innovation (Daoud Ben Arab 2021).

The measure Wojan and Bailey (1999) used to proxy input-output complexity is the Theil statistic, a measure of entropy with some similarity to Shannon's entropy which is the central component of the latent innovation measure. It has been described as a measure of the information in a system needed by agents to function effectively (Pryor 1996). In this measure, the expected informational content of an 'event' is inversely proportional to the probability of that event (p). The construction of the measure to examine its association with ISO 9000 certification assumes that the probability of selling to (buying from) another industry is defined by the share of total output sold to (bought from) other manufacturing industries. These shares are derived from the direct requirements matrix of the U.S. input-output table, and the respective probabilities can be incorporated into the computation of the Theil statistic (H) as follows:

$$H = \sum_i p_i \ln\left(\frac{1}{p_i}\right)$$

where p_i = the share of total output sold to another industry for all i in the manufacturing sector to define selling complexity, or the share of total inputs bought from another industry for all i in the manufacturing sector to define buying complexity.

Like Shannon's entropy measure the Theil statistic takes on the value of 0 in the extreme case of all output sold to (input bought from) a single industry. The other extreme is defined by output sold to (input bought from) all other industries (an upper bound of $\ln(N) = \ln(446) = 6.100$, where N is the number of all manufacturing and non-manufacturing industries from the I-O table). In the sample used in the analysis, selling complexity ranges from 0.1358 to 4.9009, buying complexity ranges from 0.8248 to 4.1707.

Empirically, the results from Wojan and Bailey (1999) parallel those of Goetz and Han (2020) in a critical respect: input-output complexity is found to be the second most important factor in predicting the outcome of interest; in this case ISO 9000 certification. The most important factor was whether the firm exported, with buying complexity the second most powerful variable based on comparison of standardised coefficients. Because the dependent variable is binary, the magnitude of the estimate can be expressed through an odds ratio. A unit increase in buying complexity increased the odds of being ISO 9000 certified by a factor of 3.76. This suggests that firms in the industry with the most complex buying relationships are 12 times more likely to be ISO certified than those in the industry with the simplest buying relationships.

If input-output complexity is strongly associated with both the opportunity for innovation and the capability for continuous improvement, then it should be strongly associated with incremental innovation in REIS. However, the usefulness of the latent innovation measure for informing other innovation survey datasets will depend on whether it demonstrates a negative association with non-innovators.

Empirical Analysis

Association Between Input-Output Complexity and Different Types of Innovation

The central empirical question is whether measures of input-output complexity constructed from secondary data are strongly associated with establishments classified as incremental innovators. Priors on the association between the latent innovation measure and classification as a substantive innovator are less clear. The latent innovation measure may predict substantive innovator membership relatively well because these firms also display many of the continuous improvement behaviours, particularly if more complex input-output relationships introduce more ideas for more far-ranging innovation. Alternatively, establishments in traditional industries producing goods for end markets subject to intense import competition where far-ranging innovation has become essential for survival would contribute to a negative association between complexity and incremental innovation. By the same token, intermediate industries with complex purchasing and selling arrangements may have less leeway for pursuing more radical innovation. The direction of association is an empirical question.

The interest in the strength of association rather than deriving a structural estimate of impact argues for a parsimonious specification. A logistic regression of incremental innovation on latent innovation would be an estimate of the gross effect of input-output complexity on the probability of innovation class membership. The comparison with the full complement of detailed industry indicator variables provides the justification for this specification where the magnitude of fixed effect coefficients is of little analytical interest.

Results from the logistic regressions using the latent innovation and industry indicator variables to explain incremental innovator, non-innovator, substantive innovator class membership are presented in Table 1. The coefficient estimates for the 46 3-digit NAICS indicator variables are not shown as is common practice. As hypothesised, latent innovation is strongly associated with the probability of being classified as an incremental innovator. The interpretation of this finding is aided by the results from the non-innovator and substantive innovator regressions. The finding that latent innovation is negatively associated with classification as a non-innovator is consistent with either explanation that buying or selling complexity induces the development of protocols required of continuous improvement or increases the opportunity for the development of new ideas. The larger negative effect of latent innovation on the probability of being classified as a substantive innovative suggests that buying or selling complexity may constrain more far-ranging innovation.

[Table 1 about here]

The regression results confirm that latent innovation based on input-output complexity illuminates one effect of industrial structure on innovation. The most interesting finding is the nonlinear effect of input-output complexity on innovation. As expected, the positive association between the latent innovation measure and incremental innovation or continuous improvement reinforces the dual opportunity-capability explanation derived from theory. Similarly, non-innovator status is negatively associated with this opportunity-capability for continuous improvement implicit in the measure. The finding that opportunity-capability for continuous improvement is also negatively associated with substantive innovation is surprising given that this class overwhelmingly responded affirmatively to the continuous improvement questions. This suggests that behaviours consistent with more far-ranging innovation may be negatively associated with input-output complexity. The ability of the latent innovation measure to isolate the intermediate stage of innovation presents a unique opportunity to examine characteristics of self-reported innovation.

To corroborate the findings with respect to latent innovation and incremental innovation we use the responses regarding product and process innovation available in REIS. Challenges to conventional wisdom that process innovation is largely incremental while far-ranging and radical innovation are much more prevalent in products cautions against simply equating process innovation with continuous improvement (Henderson and Clark 1990). However, analysis of REIS data confirms that latent innovation is positively associated with process innovation but negatively associated with product and service innovation (Table 4). The findings do reinforce a possible explanation for the negative association between buying and selling complexity and more far-ranging innovation as a coordination problem. Firms selling products or services to end-users may have much more leeway introducing non-incremental changes than intermediate product firms selling to several final product industries. The additional value this finding provides is the demonstrated usefulness of self-reported product and process innovation responses in constructing innovation profiles that are available in BRDIS and ASE.

[Table 2 about here]

Input-Output Complexity and Innovation Profiles in BRDIS and ASE

As a positive measure of innovation as prescribed by the Oslo Manual (OECD and Eurostat 2005), BRDIS and ASE do not use inferred capability in classifying innovating firms as REIS does. However, positive responses to various questions related to novelty, and product or process innovation do allow defining innovation profiles that may resemble the substantive, incremental and non-innovator classes in REIS (see Eurostat 2019). Associations with the latent innovation variable among the different profiles, and their similarity with the REIS classes provide an empirical basis for assessing how these profiles correspond to substantive and incremental innovation.

The innovation profiles available in BRDIS and ASE are defined as follows, along with their hypothesised similarity to the REIS classes:

- Substantive innovators: firms answering yes to the question ‘Sold new good or service that no other business has ever offered before,’ i.e., firms introducing new products to the market.
- Incremental innovators (type I): firms answering no to the new-to-market question above but answering yes to any other question related to new product innovation, e.g., developing products that are new to firms but not new to the market.
- Incremental innovators (type II): firms answering no to all question related to product innovation but answering yes to any question related to process innovation, e.g., new methods of manufacturing, delivery, distribution, or maintenance.
- Incremental innovators (type I and II combined): firms classified as either type-I or type-II incremental innovators. And lastly,
- Non-innovators: firms answering no to all questions related to product and process innovation.

The innovation profile to be used with the ASE and BRDIS datasets thus define five types of innovators of which three types are assumed to be incremental in nature. We assume that type-I and the combined type-I and II categories are most likely to resemble incremental innovators in the REIS dataset.

As a parallel analysis to the logistic regression with the REIS dataset, we re-estimate the model in Table 1 with the ASE and BRDIS datasets, accessed through the Federal Statistical Research Data Center (FSRDC), with respect to the five types of innovators defined above. One notable modification to the latent innovation measure is the necessity to aggregate the 6-digit NAICS measure used with the REIS dataset to the 4-digit NAICS that is available in the ASE dataset. The latent innovation measure is aggregated to 4-digit NAICS by simple averaging. We also used the 2-digit NAICS to control for industry fixed effects for the ASE and BRDIS dataset ensuring sufficiently large number of observations for each type of innovator in each industry. The REIS analysis in Table 1 was re-run with the aggregate measure and the results were similar. The only notable change was the coefficient estimate of the latent innovation variable in the non-innovator equation is positive but statistically insignificant.

The estimated coefficients using the ASE dataset are shown in Table 3. The coefficient estimate on latent innovation measure for non-innovators is positive but insignificant; that for substantive innovators is significantly negative. The coefficient estimates for type-II and the combined type-I and II incremental innovators are significantly positive but that for type-I incremental innovators is negative but not statistically significant. The coefficient estimate for substantive innovators is negative, significant, and large in absolute value.

[Table 3 about here]

The estimated coefficients using the BRDIS dataset are shown in Table 4, with the five types of innovators similarly defined with those used in the ASE analysis. The estimated coefficients on latent innovation measure for each type of innovator with the BRDIS dataset have the same signs as the ASE dataset but differ with respect to magnitude and significance. Most notably, the association between latent innovation and the innovation profiles thought to most closely resemble incremental innovators in REIS is weaker. This result is consistent with BRDIS respondents applying more stringent criteria for reporting any type of innovation due to the inclusion of detailed questions on R&D activities relative to the ASE respondent only answering innovation questions. Evidence supporting this interpretation is discussed below.

[Table 4 about here]

We observe from Tables 1, 3, and 4 the same signs of the coefficients on non-innovators, substantive innovators, and incremental innovators, except for type-I incremental innovators in the ASE and BRDIS datasets. But estimating the model separately for each dataset cannot test the statistical difference in the magnitude of these coefficients among the three datasets. For that we estimate the logistic regression models by stacking the three datasets together, assuming that incremental innovators in the REIS dataset are equivalent to either type of incremental innovator defined in the ASE and BRDIS datasets. In this model, we include the dummy variables for the samples in the ASE and BRDIS datasets and the interaction terms of the dummy variables with latent innovation measure, on which the coefficients are used to test statistical difference relative to the estimates using the REIS dataset.

However, since the ASE dataset is considerably larger than BRDIS or REIS, the results would be heavily weighted toward the ASE findings. We address this problem by stacking identically sized subsamples randomly drawn from each dataset. We randomly draw 5,000 observations without replacement from each dataset, stack these 15,000 samples, and estimate the logistic models. We repeat the process for 200 times and obtain the point estimates of the coefficients by summarizing the mean and standard deviation of the 200 set of estimated coefficients. The results are shown in Table 5.

The estimated coefficients for the ASE and BRDIS dummy variables are all statistically significant, positive for non-innovators, and negative for all types of innovators regardless of substantive or incremental type. This implies that respondents to the REIS are more likely to be classified as substantive or incremental innovators than the self-reports of innovation by type in either ASE or BRDIS. Respondents in BRDIS were most likely to not report any innovation and least likely to report innovation resembling substantive innovation relative to both REIS and ASE. This is consistent with the comparison of Norwegian innovation surveys that found that respondents in combination innovation-R&D surveys were less likely to report innovation than respondents in innovation-only surveys (Wilhelmsen 2012).[2]

The association of latent innovation measure with various types of innovators is different across the three datasets, which is visualised in Figure 1. In this figure we add the estimated coefficients on the interaction terms of latent innovation and the ASE and BRDIS dummy variables to that of the latent innovation so that the values directly reflect the magnitude of the association for each dataset. First, there is no statistically significant association of latent innovation measure with non-innovators for any dataset, as indicated by the confidence intervals for non-innovators spanning over the vertical line of zero. Second, while substantive innovators in all three datasets are negatively associated with latent innovation, the magnitude of association in the REIS dataset is the largest, followed by the ASE dataset with statistically insignificant difference. Third, all types of incremental innovators are positively associated with latent innovation, but the association using the REIS and ASE datasets is significantly higher than using the BRDIS when considering type-II and combined type-I and II incremental innovators. The difference in the association for type-I incremental innovators is statistically significant only between the REIS and ASE datasets but not with BRDIS.

[Table 5 about here]

[Figure 1 about here]

Discussion and Conclusion

Using Latent Innovation to Validate a More Restrictive Positive Innovation Measure

The positive measure of innovation as prescribed by the Oslo Manual guidance regularly identifies a majority of firms in nearly all OECD countries (Bloch and López-Bassols 2009) as having some type of product or process innovation. The lower incidence of product or process innovation in U.S. surveys relative to other OECD countries prompted cognitive testing studies to understand these national differences, with a salient difference being the extent to which novelty is considered a requisite of innovation (Peric and Galindo-Rueda 2014; Tuttle, Alvarado, and Beck 2019). Given the relative rarity of innovation using traditional measures such as patents or formal R&D expenditures, the prevalence of innovation identified through self-reported surveys may appear overly optimistic. However, the requirement that a positive measure does not impose normative assessments of success or failure will likely identify much more innovation than that passed by traditional screens. From an innovation economy perspective, where performance is a function of maximizing the number of attempts to solve problems, the focus on significant changes in products or processes regardless of success may be a

[2] One possible impact of combining a detailed R&D survey with general innovation questions as was done in BRDIS is to bias innovation rate estimates downward (Gault 2013; Wilhelmsen 2012). Because respondents to BRDIS are being asked questions about formal R&D budgets and the hiring of scientists and engineers, they may be more likely to interpret the innovation questions as pertaining to R&D-based innovation only, with resultant underreporting of grassroots or user innovation

valuable indicator.

Discussion of restricted measures of innovation to inform various policy objectives as a complement to the positive Oslo Manual measures (Gault 2018) opens the possibility of using the latent innovation measure to validate a more selective innovation indicator. This might be more in line with the concept of innovation expressed by U.S. respondents who did not perceive improvement as innovation (Peric and Galindo-Rueda 2014; Tuttle, Alvarado, and Beck 2019). The statistical evidence presented here that the latent innovation measure can isolate incremental innovation where continuous improvement is most common as distinct from the occurrence of substantive innovation or the absence of innovation makes validating a restricted indicator less ad hoc.

The innovation profiles used in this analysis of BRDIS and ASE data are also available in the Annual Business Survey (ABS), the current US innovation survey. A presumptive substantive innovator class in BRDIS and ASE defined by the ‘new to the market’ criterion performed similarly to the substantive innovator class in REIS derived from behaviours hypothesised to be consistent with more far-ranging innovation. The pooled regression analysis confirmed that responses in the innovation-only ASE that more closely resembles the ABS for firms with 10 more employees did not inflate innovation rates relative to the REIS measure. These analyses also demonstrated that the presumptive substantive innovator class in the BRDIS innovation-R&D survey appeared to apply more stringent criteria for reporting innovation. Whether the innovation rates in the innovation-R&D version of ABS, administered to microbusinesses with fewer than 10 employees, are also lower than larger businesses due to the bias identified in the ASE-BRDIS comparison could be examined by applying a regression discontinuity design to ABS data.

Published statistics from the inaugural 2018 ABS (NCSES 2022 Table 71) confirm that new-to-market innovation is relatively rare, reported by 8.9% of all companies. However, new-to-market innovation rates in innovation intensive sectors such as software publishing, precision instruments, and communications equipment are above 40%. These descriptive statistics are suggestive of the type of differentiation one would expect to see in a substantive innovation measure. The hard test of the informational value of a presumptive substantive innovation measure is the extent to which economic outcomes of interest such as export growth, revenue growth, and survivability are associated with it. These tests motivate the next stage of the research project.

References

Bloch, Carter, and Vladimir López-Bassols. 2009. “Innovation Indicators.” In *Innovation in Firms: A Microeconomic Perspective*, 21–68. Paris: OECD Publishing. https://www.oecd-ilibrary.org/science-and-technology/innovation-in-firms_9789264056213-en.

Delgado, Mercedes. 2020. “The Co-Location of Innovation and Production in Clusters.” *Industry and Innovation* 27 (8): 842–70. https://doi.org/10.1080/13662716.2019.1709419.

Deming, W. Edwards. 1982. *Quality Productivity and Competitive Position*. 1st edition. Cambridge, MA: Massachusetts Inst Technology.

Eagle, Nathan, Michael Macy, and Rob Claxton. 2010. “Network Diversity and Economic Development.” *Science* 328 (5981): 1029–31. https://doi.org/10.1126/science.1186605.

Eurostat. 2019. “Innovation Profiling in the EU, Based on CIS Data – Background and First Results.” Presented at the Working Group on Statistics on Science, Technology and Innovation, Luxembourg. Eurostat/G4/STI/WG/2019/Document 7.

Gale, H. Frederick, David A. McGranahan, Ruy Teixeira, and Elizabeth Greenberg. 1999. “Rural Competitiveness: Results of the 1996 Rural Manufacturing Survey.” 776. Agricultural Economic Report. Washington, D.C: Economic Research Service, US Department of Agriculture. https://www.ers.usda.gov/webdocs/publications/40985/19436_aer776_1_.pdf?v=6027.1.

Gault, Fred. 2013. *Handbook of Innovation Indicators and Measurement*. Cheltenham, UK: Edward Elgar Publishing.

———. 2018. “Defining and Measuring Innovation in All Sectors of the Economy.” *Research Policy* 47 (3): 617–22. https://doi.org/10.1016/j.respol.2018.01.007.

Goetz, Stephan J., and Yicheol Han. 2020. “Latent Innovation in Local Economies.” *Research Policy* 49 (2): 103909. https://doi.org/10.1016/j.respol.2019.103909.

Gómez, Jaime, Idana Salazar, and Pilar Vargas. 2016. “Sources of Information as Determinants of Product and Process Innovation.” *PLOS ONE* 11 (4): e0152743. https://doi.org/10.1371/journal.pone.0152743.

Gotzamani, Katerina D., and George D. Tsiotras. 2002. “The True Motives behind ISO 9000 Certification: Their Effect on the Overall Certification Benefits and Long Term Contribution towards TQM.” *International Journal of Quality & Reliability Management* 19 (2): 151–69. https://doi.org/10.1108/02656710210413499.

Hausmann, Ricardo, Cesar A. Hidalgo, Sebastian Bustos, Michele Coscia, and Alexander Simoes. 2013. *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. Illustrated edition. Cambridge, MA: The MIT Press.

Henderson, Rebecca M., and Kim B. Clark. 1990. “Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms.” *Administrative Science Quarterly* 35 (1): 9–30. https://doi.org/10.2307/2393549.

Hidalgo, César A., and Ricardo Hausmann. 2009. “The Building Blocks of Economic Complexity.” *Proceedings of the National Academy of Sciences* 106 (26): 10570–75. https://doi.org/10.1073/pnas.0900943106.

Hong, Lu, and Scott E. Page. 2004. “Groups of Diverse Problem Solvers Can Outperform Groups of High-Ability Problem Solvers.” *Proceedings of the National Academy of Sciences* 101 (46): 16385–89. https://doi.org/10.1073/pnas.0403723101.

Jeppesen, Lars Bo, and Karim R. Lakhani. 2010. “Marginality and Problem-Solving Effectiveness in Broadcast Search.” *Organization Science* 21 (5): 1016–33. https://doi.org/10.1287/orsc.1090.0491.

Kekezi, Orsa, and Johan Klaesson. 2020. “Agglomeration and Innovation of Knowledge Intensive Business Services.” *Industry and Innovation* 27 (5): 538–61. https://doi.org/10.1080/13662716.2019.1573660.

Moretti, Enrico. 2013. *The New Geography Of Jobs*. Reprint edition. Boston, Mass: Harper Business.

National Center for Science and Engineering Statistics (NCSES). 2020. “Annual Business Survey: Data Year 2017 (NSF 21-303).” National Science Foundation. https://ncses.nsf.gov/pubs/nsf21303/.

OECD, and Eurostat. 2005. *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*. 3rd Edition. The Measurement of Scientific, Technological and Innovation Activities. Paris: OECD Publishing. https://doi.org/10.1787/9789264013100-en.

———. 2018. *Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition*. The Measurement of Scientific, Technological and Innovation Activities. Paris: OECD Publishing. https://doi.org/10.1787/9789264304604-en.

OECD, Eurostat, and European Union. 1997. *Proposed Guidelines for Collecting and Interpreting Technological Innovation Data: Oslo Manual*. Paris: OECD Publishing. https://doi.org/10.1787/9789264192263-en.

Peric, Susan, and Fernando Galindo-Rueda. 2014. “The Cognitive Testing of Innovation Survey Concepts, Definitions and Questions, Final Report of Improving the Measurement of Innovation: Supporting International Comparisons Project.” National Center for Science and Engineering Statistics (NCSES). https://www.nsf.gov/awardsearch/showAward?AWD_ID=1114138.

Pryor, Frederic L. 1996. *Economic Evolution and Structure: The Impact of Complexity on the U.S. Economic System*. Cambridge ; New York: Cambridge University Press.

Shannon, C E. 1948. “A Mathematical Theory of Communication.” *The Bell System Technical Journal* 27: 379–423, 623–56.

Tuttle, Alfred D, Herman A Alvarado, and Jennifer Beck. 2019. “OECD Innovation Project: Findings From Early Stage Scoping Interviews In The United States Final Report.” 2019–05. Research Report Series: Survey Methodology. Washington, D.C: US Census Bureau.

https://www.census.gov/content/dam/Census/library/working-papers/2019/adrm/rsm2019-05.pdf.

Wilhelmsen, Lars. 2012. “A Question of Context: Assessing the Impact of a Separate Innovation Survey and of Response Rate on the Measurement of Innovation Activity in Norway.” Oslo, Norway: Statistics Norway. https://www.ssb.no/a/english/publikasjoner/pdf/doc_201251_en/doc_201251_en.pdf.

Wojan, Timothy R. 1998. “Spatial Diffusion of Management Practices in Urban and Rural Areas.” *Growth and Change* 29 (3): 319–43. https://doi.org/10.1111/0017-4815.00090.

———. 2016. “Towards a More Reliable Substantive Innovation Measure from Self-Reported Surveys: Hard Tests of the 2014 Rural Establishment Innovation Survey Latent Class Analysis.” OECD Blue Sky Forum on Innovation Indicators. Organisation for Economic Cooperation and Development (OECD). https://www.oecd.org/sti/193%20-%20SelfReportedInnovationSurveys_IncreasingReliability_ClearedManuscript.pdf.

Wojan, Timothy R., and Thomas Bailey. 1999. “International Quality Control Certification: Signal or Heuristic?” https://www.researchgate.net/publication/2614786_International_Quality_Control_Certification_Signal_or_Heuristic.

Wojan, Timothy R., Daniel Crown, and Anil Rupasingha. 2018. “Varieties of Innovation and Business Survival: Does Pursuit of Incremental or Far-Ranging Innovation Make Manufacturing Establishments More Resilient?” *Research Policy* 47 (9): 1801–10. https://doi.org/10.1016/j.respol.2018.06.011.

Wojan, Timothy R., and Bonnie Nichols. 2018. “Design, Innovation, and Rural Creative Places: Are the Arts the Cherry on Top, or the Secret Sauce?” Edited by Mark A. Runco. *PLOS ONE* 13 (2): e0192962. https://doi.org/10.1371/journal.pone.0192962.

Wojan, Timothy R., and Timothy Parker. 2017. “Innovation in the Rural Nonfarm Economy: Its Effect on Job and Earnings Growth, 2010-2014.” 238. Economic Research Report. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/publications/pub-details/?pubid=85170.

Wojan, Timothy R., and Timothy F. Slaper. 2020. “Are the Problem Spaces of Economic Actors Increasingly Virtual? What Geo-Located Web Activity Might Tell Us about Economic Dynamism.” *PLOS ONE* 15 (9): e0239256. https://doi.org/10.1371/journal.pone.0239256.

Appendix

Data description

The dependent variables in the logistic regression are from the REIS, BRDIS, and ASE datasets accessed through the Federal Statistical Research Data Center (FSRDC). Table A1 shows the frequency of each type of innovative firms in each dataset.

[Table A1 about here]

The industry-level latent innovation measure is calculated based on Goetz and Han (2020). The original measure is at the 6-digit NAICS level that is used in the logistic regression in Tables 1 and 2, and we aggregate it the 4-digit level used in the regression in Tables 3–5. Table A2 shows the summary statistics of this variable.

[Table A2 about here]

Tables

Table 1: Logistic Regression of Innovator Class Membership on Latent Innovation and Industry Indicators

Parameter	Non-Innovator	Substantive Innovator	Incremental Innovator
Intercept	-0.00233	-2.7381	-0.4005
Latent Innovation	-0.1295	-0.778	0.7627
	(<0.0001)	(<0.0001)	(0.0001)
Odds Ratio	0.879	0.459	2.144
Industry FE	Yes	Yes	Yes
Percent Concordant	54.3	60.4	55.5
Percent Discordant	42.7	37.3	41.5
Percent Tied	3.1	2.3	3
Linear Probability Adj R2	0.0152	0.0349	0.017

Source: Authors using data from the 2014 ERS Rural Establishment Innovation Survey and Goetz and Han (2020). Note: p-values in parentheses.

Table 2: Self-reported Product, Service, and Process Innovation and Latent Innovation

Parameter	Self-Reported Product Innovation	Self-Reported Service Innovation	Self-Reported Process Innovation
Intercept	0.1452	1.0841	1.3287
Latent Innovation	-0.8343	-1.2845	0.343
	(<0.0001)	(<0.0001)	(<0.0001)

Odds Ratio	0.434	0.277	1.409
Industry FE	Yes	Yes	Yes
Percent Concordant	66.8	63.2	62.1
Percent Discordant	30.6	33.8	35.3
Percent Tied	2.6	3	2.6

Source: Authors using data from the 2014 ERS Rural Establishment Innovation Survey and Goetz and Han (2020).

Note: p-values in parentheses.

Table 3: Estimation of logit models with the ASE dataset

Parameter	**Non-innovators**	**Substantive innovators**	**Type I incremental innovators**	**Type II incremental innovators**	**Type I and II incremental innovators**
Intercept	0.8827 ***	-3.417 ***	-1.584 ***	-2.417 ***	-1.068 ***
	(0.056)	(0.1629)	(0.0677)	(0.0866)	(0.0576)
Latent innovation	0.0208	-1.016 ***	-0.0405	0.7295 ***	0.2142 ***
	(0.0526)	(0.1109)	(0.0588)	(0.094)	(0.0542)
Odds ratio	1.021	0.362	0.9603	2.074	1.239
Industry FE	Yes	Yes	Yes	Yes	Yes
AIC	1.504e+05	4.456e+04	1.272e+05	6.789e+04	1.45e+05
BIC	1.505e+05	4.468e+04	1.273e+05	6.801e+04	1.451e+05
Log Likelihood	-7.52e+04	-2.227e+04	-6.358e+04	-3.393e+04	-7.249e+04
Deviance	1.504e+05	4.454e+04	1.272e+05	6.787e+04	1.45e+05
Num. obs.	125000	125000	125000	125000	125000

*Source: Authors using data from the 2014 Annual Survey of Entrepreneurs. Notes: Standard errors in parentheses. Industry fixed effect are controlled with 2-digit NAICS. All numbers in this table are rounded based on the rounding rules of the FSRDC. Significance level: *** for 1%, ** for 5%, * for 10%.*

Table 4: Estimation of logit models with the BRDIS dataset

Parameter	**Non-innovators**	**Substantive innovators**	**Type I incremental innovators**	**Type II incremental innovators**	**Type I and II incremental innovators**
Intercept	0.6064 ***	-2.365 ***	-3.841 ***	-1.041 ***	-0.9763 ***
	(0.0532)	(0.0899)	(0.1474)	(0.0645)	(0.0604)
Latent innovation	0.0944	-0.5275 ***	-0.0664	0.1532 *	0.117
	(0.0726)	(0.1241)	(0.1962)	(0.0885)	(0.0826)
Odds ratio	1.099	0.590	0.936	1.166	1.124
Industry FE	Yes	Yes	Yes	Yes	Yes
AIC	3.769e+04	1.69e+04	8003	2.819e+04	3.117e+04
BIC	3.772e+04	1.692e+04	8028	2.821e+04	3.119e+04
Log Likelihood	-1.884e+04	-8446	-3998	-1.409e+04	-1.558e+04
Deviance	3.769e+04	1.689e+04	7997	2.818e+04	3.116e+04
Num. obs.	35500	35500	35500	35500	35500

*Source: Authors using data from the 2014 Business R&D and Innovation Survey. Notes: Standard errors in parentheses. Industry fixed effect are controlled with 2-digit NAICS. All numbers in this table are rounded based on the rounding rules of the FSRDC. Significance level: *** for 1%, ** for 5%, * for 10%.*

Table 5: Estimated logit models using three datasets: 5,000 random samples from each dataset

Parameter	Non-innovators	Substantive innovators	Type I incremental innovators	Type I and II incremental innovators	Type II incremental innovators
Intercept	-0.1755	-1.818***	-0.3783***	-0.6484***	-0.5849***
	(0.1159)	(0.2297)	(0.0939)	(0.1039)	(0.107)
BRDIS	1.82***	-1.874***	-3.316***	-0.9814***	-1.001***
	(0.1275)	(0.1788)	(0.164)	(0.1319)	(0.141)
ASE	0.9932***	-1.37***	-0.591***	-0.2744**	-2.301***
	(0.1061)	(0.1653)	(0.1077)	(0.1242)	(0.2542)
Latent innovation	-0.0616	-1.274***	0.5988***	0.8659***	1.078***
	(0.1414)	(0.1674)	(0.1434)	(0.1377)	(0.1451)
Latent innovation * BRDIS	0.0126	0.93***	-0.1951	-0.7403***	-0.9861***
	(0.183)	(0.284)	(0.2689)	(0.2177)	(0.232)
Latent innovation * ASE	-0.1666	0.1453	-0.3995***	-0.2273	0.2162
	(0.1304)	(0.2538)	(0.1375)	(0.1528)	(0.3477)
Industry FE	Yes	Yes	Yes	Yes	Yes

*Source: Author using 2014 ERS Rural Establishment Innovation Survey, 2014 Annual Survey of Entrepreneurs, and 2014 Business R&D and Innovation Survey. Notes: Standard errors in parentheses. The estimates are based on 200 repetitions of random sampling of 5,000 observations from each dataset. The point estimates and standard errors are the mean and standard deviation of the 200 set of estimated coefficients. All numbers in this table are rounded based on the rounding rules of the FSRDC. Significance level: *** for 1%, ** for 5%, * for 10%.*

Table A1. Frequency of each type of innovative firms in three datasets

	REIS	BRDIS	ASE

	Count	Percent	Count	Percent	Count	Percent
Non-innovators	4,200	39.3%	27,500	77.4%	80,500	64.5%
Substantive innovators	1,900	17.8%	2,300	6.5%	5,900	4.7%
Incremental innovators	4,600	43.0%	–	–	–	–
Incremental innovators type I	–	–	850	2.4%	28,500	22.8%
Incremental innovators type II	–	–	4,900	13.8%	10,000	8.0%

Notes: All numbers in this table are rounded based on the rounding rules of the FSRDC. The counts are based on unweighted samples.

Table A2. Summary statistics of latent innovation measure

	Mean	Std	Min	Median	Max
Latent innovation, 6-digit NAICS	0.52	0.25	−0.18	0.48	0.94
Latent innovation, 4-digit NAICS	0.52	0.23	0.10	0.47	0.94

Figures

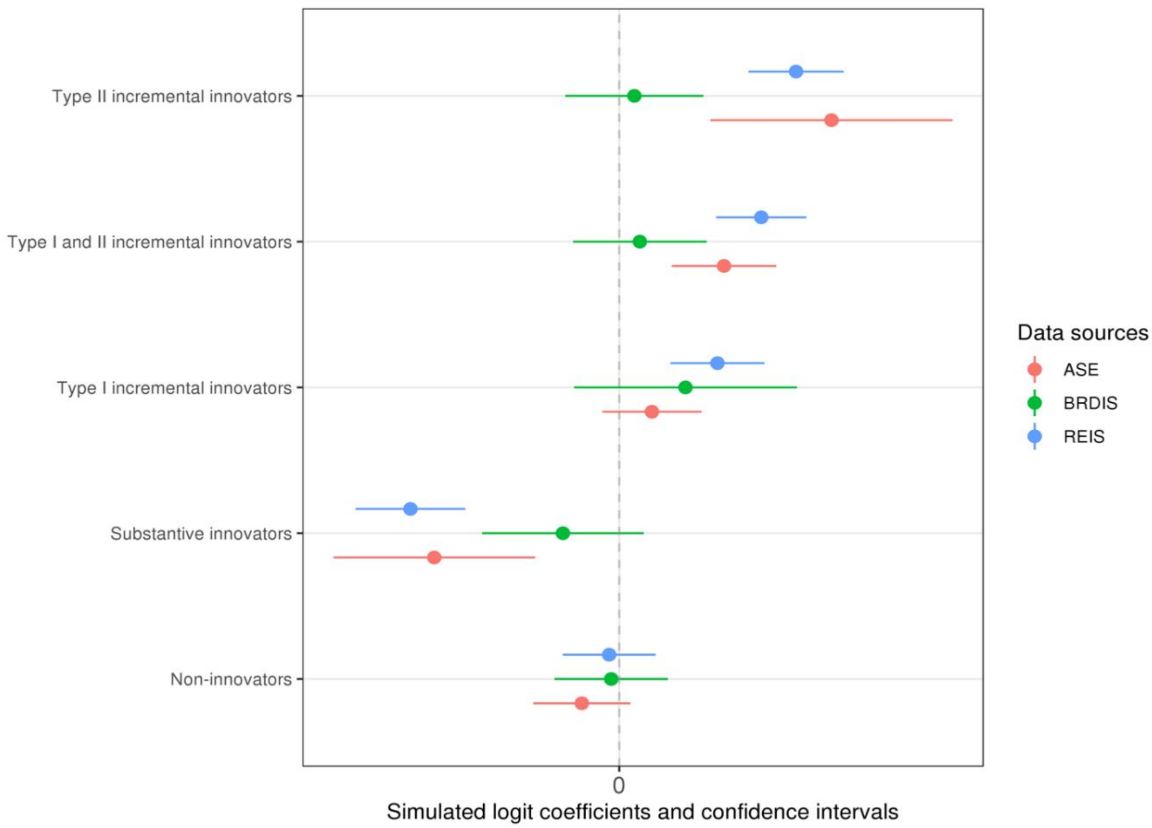

Figure 1. Comparison of the estimated association of latent innovation measure with each type of innovators using three datasets. The points represent the point estimates in Table 5 and the error bars represent the 95% confidence intervals. All numbers are rounded based on the rounding rules of the FSRDC.